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It's a journey: from media effects to dynamic systems

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ABSTRACT

This paper aims to demonstrate how an analytical paradigm shift from the General Linear Model (GLM) used in most communication processes and effects research to dynamic systems theory (DST, a nonlinear mathematical theory), fundamentally changes one's research assumptions and research questions and leads to novel approaches to research design, data collection, and analysis. Concrete examples demonstrating these changes are drawn from the co-viewing literature. In addition, we discuss how data collected and interpreted using the GLM can be re-analyzed and re-interpreted to further inform our understanding of communication behavior when we use the assumptions of dynamic systems theory to derive new predictions.

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The past decade has seen a growing interest among social scientists in using dynamic systems theory (DST), also called complexity or chaos theory, instead of the general linear model (GLM) as an analytical framework for understanding evolved, embedded, embodied human behavior. A great deal of work in the natural sciences is now using the assumptions and concepts of DST, rather than the GLM. The body of DST inspired psychological research in areas such as perception, cognition, learning, memory, and development, to name a few, is growing fast (Beebe et al., 2016; Beer, 1996; Bingham, 2004; Kelso, 1995; Oudeyer & Smith, 2016; Port & Van Gelder, 1995; Thelen & Smith, 1994). Recently communication researchers studying organizational, interpersonal, and mass communication have also begun to at least discuss and sometimes to actually re-conceptualize their theories using the assumptions of the DST rather than the GLM (e.g., Andras, Roberts, & Lazarus, 2003; Hoffman, 2008; Lang, 2013; Lang & Ewoldsen, 2010; Lang et al., 2018; Salem, 2013; Sherry, 2015a) and to develop DST inspired methodological tools to test those new theories (e.g., Buder, 1991; Coco, & Dale, 2014; Corman, 1996; West & Biocca, 1996).

To understand the emerging dynamic systems perspective, communication scholars need to grapple with the ways in which its fundamental assumptions and its conceptualization of change are completely different from those of the GLM. The goal of this paper is to identify and describe

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these differences in the nature and causality of change between DST and the GLM (the primary analytical tool in our field) and then to demonstrate why adopting DST leads inevitably to change in all aspects of theory development and research design. We will provide concrete examples from the co-viewing literature of how changing one's fundamental assumptions about the nature of change alters theoretical assumptions and questions, leading to different research designs, analytical strategies, and results.

Communication research: GLM or DST?

How the GLM drives theoretical assumptions in media processes and effects research

For the past fifty years, the GLM has been the primary analytical tool used in social scientific research attempting to understand the processes and effects of communication messages. The GLM underlies common analyses like t-tests, regression, analysis of variance, structural equation modeling, and multi-level modeling (Babbie, 1998, 2015; Wrench, Thomas-Maddox, Richmond, & McCroskey, 2008). When we use the GLM, we are accepting the GLM's assumptions about the nature of our variables and the nature of causation, so we need to be aware that when these assumptions are not met, the validity of our findings is uncertain. Some primary assumptions made when using the GLM are that relationships among variables are *assumed* to be linear, that *all* the variables in a model are normally distributed, that the independent variables are *not* correlated with one another, and that variance is *evenly distributed* across the range of the dependent variable. When these mathematical assumptions are combined with the theoretical assumptions of the dominant processes and effects paradigm, it means that we assume certain things about people and about change.

Media psychologists are interested in how media change people and in explicating the dynamic processes that occur after encountering a media message until the completion of the resultant change. We conceptualize humans as relatively stable and media as external causal agents of change in attitudes, thoughts, and behaviors (Lowery & DeFleur, 1983, 1988, 1995; Sparks, 2002). Studies are designed to identify causal unidirectional additive linear effects and estimate their effect sizes because that is what the GLM does. When using the GLM, we accept that what we are looking for is linear and additive (Livingstone, 1996; Valkenburg, Peter, & Walther, 2016). Linear effects are those in which change in the independent variable produces a proportionate change in the dependent variable. Dependent variables are assumed to be continuous and to have equal variance around the mean for their entire range (called homoscedasticity). Researchers using the GLM are looking for linear relationships between message content and outcome variables (e.g. emotion, memory, attitude, behavior). The percentage of variance explained by each independent variable is then added up to explain some percentage of the outcome. It is a reductionist approach which assesses the portion of causality attributable to each of many theorized causes seeking ultimately to explain the totality of the effect. The paradigm directs researchers to search for and add up the elements of media that change audiences' thoughts and behaviors (e.g., McQuail, 1977; Scheufele & Tewksbury, 2007).

There is no doubt that communication researchers engaging in Kuhnian normal science under this paradigm have learned a lot about communication at both macro and micro levels (Neuman & Guggenheim, 2011; Perloff, 2013; Potter, 2012; Sherry, 2015b). The focus of existing media processes and effects research ranges from media psychological approaches which examine the ability of media to change attitudes, behaviors, beliefs, emotion, cognition, and decision making (Nabi & Oliver, 2009), to media sociological approaches which investigate media effects at economic, political, and social levels (Benson, 1995; Gitlin, 1978). We have developed many influential communication theories and models (e.g., Berlo, 1960; Petty & Cacioppo, 1986; Schramm, 1954; Shannon & Weaver, 1949; Witte, 1994). We have recognized reciprocal causal relations between media and individuals and between message producers and receivers (e.g., Bandura, 1994; Slater, 2007). We have considered how message processes and effects change over time, over different time scales, and last for different amount of time (Keene & Lang, 2016; Wang & Lang, 2012; Wang, Lang, & Busemeyer, 2011). We have incorporated a variety of new methodologies to investigate these time-relevant research questions such as time series analysis and multilevel modeling (Watt & VanLear, 1996).

Nevertheless, despite this effort we are not coalescing around a general theoretical approach or a set of agreed upon conclusions. Instead we have a proliferation of theories and research about media processes and effects (Gitlin, 1978; Livingstone, 1996) whose primary conclusion is, to quote one of our colleagues, "it depends and it's complicated.[1]" (Huesmann & Malamuth, 1986; Livingstone, 1996; Valkenburg et al., 2016). There is also concern about the generality and size of the effects uncovered. Even complex dynamic models with many proposed causal mechanisms and processes add up to explain only a tiny portion of the variance in our dependent variables (e.g. Rasmussen, Keene, Berke, Densley, & Loof, 2017). And yet it is difficult to look at the world and agree with our research that media effects are small and unstable. This paper suggests that one reason our research is not adding up may be that human communication behavior is not linear and additive and as a result the sum of its parts does not add up to equal the whole. If that is so, and we continue to use an analytical tool that insists that they are and can only tell us how well they behave *as if* they are, we are doomed to failure.

A comparison of the GLM and DST

DST is a mathematical theory that can be used to test causal predictions about change in any area of study. However, its assumptions are antithetical to those of the GLM. First, DST is a system theory (Strogatz, 1994). While external factors can influence how the system behaves, the causal structure of its behavior is part of the system. To study communication using DST, one must identify a communication system to study (e.g. a human, watching a TV in a safe place, or a human playing a game on their phone in their car, etc.). This means that the message is not external to the human because the human and the message are part of the same system.

Second, DST does not assume that humans are necessarily stable. Rather it assumes that systems change over time and that behaviors range from extremely unstable (easy to change) to extremely stable (hard to change). One of the requirements for being a dynamic system is that the system cannot be energetically balanced (i.e. at equilibrium) rather dynamic systems require energy inputs to support change. Varying the level of energy input is a major parameter that can drive change. All systems have a final behavioral state (or behavioral attractor, Strogatz, 1994) into which the system will settle when the energy runs out. For human systems, that ultimate point attractor is death.

Third, DST does not assume proportionate change in independent and dependent variables (i.e. linearity) nor the associated reductionist assumption that the whole is equal to the sum of its parts. Rather it assumes non-linearity which means that adding up the parts will *not* equal or explain the system. Instead causality must be understood within the context of a system shifting suddenly among a set of qualitatively different behavioral states in response to concomitant changes in other aspects of the system. Systems have a set of behaviors they can exhibit at any given time (called the *state space*) and sudden shifts from one to another are called *phase shifts* (Strogatz, 1994). All possible system behaviors are not available at all points in time. Systems are said to undergo a bifurcation at points in time where one set of available behaviors changes with some or all of the previous behaviors disappearing and sometimes new behaviors appearing (Strogatz, 1994).

Fourth, DST clearly does not require dependent variables with equal variance across their range since the behavior of the system in DST (the dependent variable) is assumed to be categorical, not continuous. Nor does it require normality of independent variables because it does not capture evidence of change by averaging across groups. In fact, DST makes no assumptions about variability because DST is designed to explain change by capturing regularities in the variability of the system. Because behaviors are categorical and each member of the system can only engage in one behavior at a time, there are two kinds of variability that are used to understand change in the system: individual variability which is the quality of performance of those behaviors within an individual over time and system variability which is the variability in behaviors exhibited by the system's members at a given point in time. DST techniques are designed to assess these two types of variability, not to compare the central tendency of a group of people on one variable at different levels of another variable. The variability in performance of a behavior by a given member of a system is used as an indicator of the stability of that behavioral attractor for that individual. When a phase shift from one behavior to another is imminent, performance variability increases until the phase shift occurs. After the phase shift, variability decreases as the stability of the new behavior increases. One way to measure variability in the occurrence of each of the possible behaviors in a system is to count the number of individuals exhibiting each behavior at a given time, the more people, the more stable the behavior. Stable behaviors are called deep attractors while unstable behaviors are weak attractors.

If you decide to study communication using DST, then the steps in your analysis as well as your theoretical assumptions about the nature of your variables, causality, and variability must change. To understand change using DST requires first, that you define the system you are studying, identify all its possible behavioral states, and discover their relative stability. These, like all aspects of the system can only be determined over time. Therefore, a dynamic system can only be described, analyzed and understood over time. The standard practice of measuring a beginning state at a single point in time, then, administering a stimulus of some duration, and then observing an outcome variable at a single point in time cannot determine the stability of either the beginning state or the end state, nor can it observe the change (that is the loss of stability, shift to a qualitatively different state, and increase in stability that makes up change in DST) as it occurs. The change in a dynamic system cannot be understood as the sum of small differences caused by a set of variables between the beginning and the end of the experiment. Rather, it is the story of emergent change that unfolds over time as a result of the dynamic interactions of the changing elements of the system and in response to external variables (called *control parameters* in DST) that alter the actions of the system. To further illustrate this argument, let's use an example from the motion perception literature. Johansson (1973) highlighted a man's outline using a number of illuminated dots and used these point-light displays to show how humans move. When people saw the displays at a single point in time, e.g. not moving, participants could not tell what they were. However, when they were presented in sequence (as a video), people could recognize a person walking, jumping, running, etc. What we want to argue here, is that GLM inspired communication research captures only a few snapshots of one or two variables along the dynamic trajectory of behaviors. Because we can't see the entire set of points over time, we may not be able to detect general patterns of communication behavior, just as observers of point-light displays could not see a shift from walking to running unless they saw the system functioning over time.

The early stages of a dynamic systems analysis may be more qualitative than quantitative requiring the actual observation of a system over time to understand its possibilities. Consider a concrete example of a dynamic system involving a group of people watching a stimulus. Imagine you are observing a large group of people – but you don't know what they are doing. As you watch, people are doing all sorts of different things, they are chatting with one another, talking on their phones, closing their eyes in repose. Suddenly you hear a thwack, after which most members of the crowd all look simultaneously to the left, then to the right, then to the left, then to the right, then they cheer, and go back to doing a bunch of different things. What has just happened?

Probably you guessed this crowd is watching a tennis match. As we begin to watch them, they are all in variously different states, there is no emergent behavior in the dynamic system we are observing which is made up of the crowd, the players, and the ball in a stadium. Then, one of the players serves the ball and both the crowd's and the players' behavior is organized by the ball. When the point ends, the crowd returns to an unorganized (called chaotic) state. Here we see an emergent behavior because most members of the crowd are there with the goal of watching the tennis match. When the ball is in play, synchronized watching behavior emerges. When the ball is not in play, it disappears. Some people in the crowed may not have the goal of watching the match. Close observation will find those people because they do not take part in the synchronized watching behavior.

By observing this system over time, we are beginning to identify the system's state space (i.e. its set of possible behaviors). So far we have seen two qualitatively different behavioral states: 1) people are doing seemingly random things and 2) most are engaging in synchronized watching. These two qualitatively different behaviors are attractor states for this system and they change suddenly from one state to another. The one in which most people engage at any given time is the more stable state for the system. When there is no ongoing point, doing random things is the stable state or deep attractor. As soon as the point begins, the synchronized watching behavior emerges and becomes the deep attractor.

It is the thwack of the ball that causes the shift from chaos to synchronized watching. In DST, the thwack of the ball can be thought of as a perturbation of the system, and for most people in the crowd that perturbation moves them from the uncoordinated state to the synchronized watching state. For those individuals, as long as the ball is in play, the synchronized watching state is more stable than the doing something else state. For the people who do not watch, what they are doing between points is the more stable attractor and the perturbation of the system caused by the thwack of the ball fails to shift them into the synchronized watching behavior. From this example we see the two kinds of stability introduced earlier: system stability which tells us which behaviors are deeper or shallower attractors at a given time, and second, individual stability which tells us which behaviors are more or less deep for a given individual.

To summarize, a DST analysis requires us to identify the system (ball, crowd, players, and stadium), identify the state space (unorganized, synchronized watching), assess the depth of the system's behavioral attractors at a given time and assess the stability of the behaviors within individuals (Thelen & Smith, 1994). The next step in a DST is to search for the initial conditions of the various parts of the system that have strong influences on the system's behaviors. The most obvious in this example is each crowd member's initial goal (to watch the match or not to watch the match). This is an initial condition that strongly influences individual behavioral stability.

Moving on, the next step is to identify parameters within and outside the system that move the system from one stable state to another. There are two categories of parameters according to DST. The first type of parameter is called an *order parameter*. Order parameters are variables internal to the system which capture or slave the behavior of some parts of the system thereby reducing its complexity (i.e. degrees of freedom, Haken, 1977). In this example, the ball acts as an order parameter slaving members' visual perceptual systems which results in the synchronized watching behavior. The second group of parameters called *control parameters* (Thelen & Smith, 1994) are linear continuous variables external to the system that cause the system to move from one behavior to another within its state space. One possible control parameter in the tennis example is the light level. As day goes to night, the amount of light decreases. If the stadium is not lit, darkness will increase until the ball can no longer be seen and the organized watching behavior will cease. As light level changes in a linear fashion, the behavior of the crowd will become more variable (and therefore less stable) as a function of individual differences in the ability to see in the dark, until most people cannot see and the chaotic attractor will return.

Communication as a complex dynamic system

So having applied DST to a tennis match, how do we go about applying it to communication? What does it mean to say that communication is a complex dynamic system? At a minimum it must have communicators, embedded in a context, acting over time. Because it is a system, change in any part of the system can lead to changes in the qualitative behavior of the overall system. Communication is a good candidate for dynamic systems analysis because it involves many systems operating at different time scales and changing over time. Hence it is inherently dynamic. Human beings are nested dynamic systems with thousands of degrees of freedom. The various nested systems of the human, the changing aspects of the environment, and change in message content and structure are all operating at different timescales which means that their interactions are likely to be characterized by nonlinearity and bidirectional interactions between faster (e.g. neurological) and slower (e.g. cultural) systems (Eiler, Kallen, Harrison, & Richardson, 2013).

The tennis example demonstrates why a switch to DST requires us to change our questions from "does input x cause output y" to "what is my system," "what are its possible behaviors," "what initial conditions matter," "can I identify order and control parameters." It also makes clear that our analytical approaches must change. If our analyses average over people at a time and within people over time, we will lose the dynamics of stability, instability, and change both within the system as a whole and within an individual over time. Similarly, if we do not allow context to change, or assess the influence of initial conditions, we will be unable to observe all of the system's behaviors in order to identify its attractors and assess their stabilities. Therefore, the focus for DST researchers is on the *variability* of the system across and within individuals over time, *not* averages. We need to learn how to examine *patterns* of states and *patterns* of variability, accessible both through qualitative inspection of data, linear analysis where appropriate, and the use of nonlinear analysis and modeling when possible. To study communication as a property of a dynamic system, we must learn to observe the system over time and in different conditions in order to discover what the system can do. Only then can we analyze how system does what it does. In summary, the goal of communication inquirers taking a DST approach is not to ask if there is change but instead to describe, understand and eventually model and predict that change.

Putting dynamics and systems into television co-viewing

Television co-viewing studies investigate how co-viewing changes people's cognitive, experiential, and behavioral responses to messages (e.g., Haridakis & Hanson, 2009; Zillmann, Weaver, Mundorf, & Aust, 1986). Early co-viewing research, done in the context of family viewing, examined how parent-child co-viewing altered learning (Brown & Cantor, 2000; Cantor & Wilson, 1984; Valkenburg, Cantor, & Peeters, 2000; Wilson, Hoffner, & Cantor, 1987; Wilson & Weiss, 1993). Because co-viewing is inherently dynamic and involves multiple people in a specific context interacting with one another and with a message over time, it is easily reconceptualized as a dynamic system and its results can be reinterpreted as qualitatively different behaviors whose stability vary and which change over time. The co-viewing system consists of two or more co-viewers, at least one media message, and at least one message deliverer (e.g. television). This system affords human-message interaction and interpersonal interaction. Those two communication processes occur simultaneously and continuously impact one another, leading to emergent behaviors within this nonlinear complex dynamic system. In this section, we will conceptualize television co-viewing from a *linear* perspective, from a linear *dynamic* perspective, and finally from a *nonlinear* dynamic *systems* perspective. For each perspective we will provide examples from the literature that illustrate how changing assumptions changes research questions, designs, and analytical strategies.

Co-viewing as a linear effect

The primary linear co-viewing research question is "do the effects of viewing a television message on outcome variables differ in the single verses the co-viewing context?" The independent variable/cause is whether you are viewing alone or in a group. The dependent variables are the outcome variables of interest. The analysis strategy is to examine the significance of post viewing mean differences of the outcome measure between conditions. It is important to note that, this approach is focused on the significance, not the size, of the mean difference. Significance is best achieved when there is less variability around the mean. Various controls are often placed on the experiment (e.g. neutral programming, same sex or age co-viewers, etc.) to reduce the variability around the mean (Kirk, 2013). When found, significant mean differences are interpreted as meaning that co-viewing caused a change in an outcome variable.

For example, several studies have assessed the effect of co-viewing on enjoyment (Harris & Cook, 2011; Lull, 1980; Zhu, Heynderickx, & Redi, 2015) predicting that co-viewing increases enjoyment. Participants report their enjoyment *after* viewing a television stimulus alone or in pairs. On average, people report more enjoyment after co-viewing. A DST analysis would begin by "observing" single viewers and co-viewers and measuring how much time each viewer spent in an enjoyment state and in a non-enjoyment states to determine the stability of each behavior in each condition for each person. They would also count the number of people in enjoyment or non-enjoyment states at each point in time. The prediction is that individuals will spend more time in enjoyment states when co-viewing and less time in enjoyment states when alone (i.e. when co-viewing enjoyment will be a more stable attractor for individuals). Another prediction is that at any given time more people will be in the enjoyment condition when viewing in pairs compared to alone. It is worth noting here that dynamic data collected in an experiment designed to use the GLM can be reanalyzed using the DST. For example, suppose you had a dynamic measure of enjoyment (e.g. activation in the smile muscle), which was previously averaged over time and people to assess enjoyment. You could determine reasonable ranges of the variable that corresponded to enjoying and not enjoying and a midrange where one state is destabilizing and the other is stabilizing. Then you could measure the time for each person in each condition in each state and see if enjoyment is more stable within individuals over time or at a given time within the system as predicted. The DST researcher would also predict that the effect would not be there for all individuals or for the system at all times. By identifying those people for whom enjoyment is a deeper attractor, one could begin the hunt for initial conditions, control parameters and order parameters that change the stability of the enjoyment attractor.

Co-viewing research has also investigated other important aspects of a complex system such as differences in an individual's histories and initial conditions. For example, Banjo and colleagues (Banjo, 2013; Banjo, Appiah, Wang, Brown, & Walther, 2015), asked if black and white viewers reported different levels of favorable attitudes, perceived bias against blacks, excitement and absorption after viewing black-oriented comedies and films with in-group (black-black/white-white) compared to out-group (black-white) co-viewers. Here, something about the individual (race), something about the context (race of co-viewers), and something about the message (black-oriented videos) are all considered when assessing the influence of co-viewing. Results showed that blacks believed that viewing black films would be perceived more negatively by whites than by blacks, and reported greater excitement, more favorable attitudes, and greater absorption in the program when co-viewing with in-group members. White viewers' experiences did not differ as a function of co-viewer race. While these findings are interesting, we don't know the pattern of behaviors among white viewers that leads to that average. What if the dependent variable was bi-modal and half of the whites enjoyed themselves more when viewing with out-group members and half enjoyed themselves less. If two stable behaviors with relatively equal depth occur simultaneously, and one does not look at variation of the behaviors under observation either across time or across people, one simply cannot be at all sure that the final mean is in fact the central tendency of a normally distributed variable which has equal variance at all levels of the independent variable.

Assuming time matters – linear dynamic media effects approach

Recently, processes and effects researchers have begun to embrace the inherently dynamic nature of communication by using dynamic measures to track and model behaviors during message viewing. For example, Wang and colleagues (Wang et al., 2011, 2014) analyze not the mean of the outcomes but rather the trajectory of outcome variables before, during, and after message interaction. This approach allows us to investigate how message change causes behavior change. This approach is most common in work using psychophysiological measures where message changes are time locked to physiological responses to identify aspects of messages that increase attention or elicit emotional responses (e.g., Potter & Bolls, 2012; Rasmussen et al., 2017; Ravaja, 2004). However, because this work uses the GLM to analyze the data, it is still taking a linear approach. For example, Lang, Sanders-Jackson, Wang, and Rubenking (2013) demonstrated different trajectories of attention and memory for messages that were, over time, increasingly positive, increasingly negative or simultaneously increasingly positive and negative. Because they used GLM, these trajectories are created by averaging across subjects at each time point regardless of differences in initial conditions and individual history. A DST analysis, however, would assume the possible existence of qualitatively different trajectories and therefore begin by observing individuals to determine the number of different trajectories demonstrated (i.e. the state space of the system), after which one could determine the system stability of each behavior (by counting the number of people engaged in each) and the within individual stability of each behavior (by counting the number of seconds each person spent engaged in each behavior).

A co-viewing example of how changing from a static to a linear dynamic approach changes research design, measurement, and findings can be found in another study examining black viewers' excitement and absorption while watching a black-oriented comedy with in- or out-group co-viewers. Banjo et al. (2016) assumed time spent interacting mattered and so they measured attention (absorption) and emotional arousal (excitement) over the course of a stimulus presentation, resulting in two sets of time series data. Thus, they did not average their variables over time, though they still averaged them across groups. This makes sense since they were looking to see if blacks and whites had different trajectories indicative of qualitatively different behavioral states (e.g. more excitement and enjoyment vs. less excitement and enjoyment). Using time series analysis, they found that the two groups did have different emotional trajectories. Out-group compared to in-group black viewers had larger increases in emotional arousal and larger decreases in attention over the course of the message. In contrast, out-group compared to in-group white viewers exhibited a small decrease in emotional arousal and a small increase in attention. From this study we can see that if one makes a DST assumption, these two groups will have qualitatively different behaviors, one can use linear dynamics to test for the predicted difference. However, if one makes DST assumptions, one would also want to look at the existence and distribution of trajectories within groups to identify the number and depth of other attractors that might exist.

Now assume non-linear dynamic change – a DST approach

To do this, we must first conceptualize the dynamic system we are trying to understand. What are the parts of the co-viewing system? Most DST approaches to communication begin with a human interacting over time with a message delivered by a human or a medium in some context. In television co-viewing, we know we are interested in manipulating a contextual variable (presence or absence of other humans) and examining how it changes the over-time interaction between a human and a television message. Rather than assuming that things are increasing or decreasing in a linear fashion over time, we are looking for qualitative changes in behaviors over time within individuals, and over-time shifts in the distributions of individuals within those qualitative states. What are those qualitative states or, what is the state space of the co-viewing system?

Let's consider the variables used in the previous examples, enjoyment, attention, and arousal. We are used to thinking and measuring them as things that are continuously increasing and decreasing. Now let's assume they are not. Consider attention. Maybe attention does not increase and decrease smoothly. Perhaps we have only a few qualitatively different attentional behavioral sets. For example, we might have a state of boredom (characterized by low appetitive activation), a state of engagement (characterized by mild appetitive activation), a state of involvement (characterized by moderate appetitive activation), and a state of flow (characterized by high appetitive activation). In this case we see a possible linear control parameter (i.e., appetitive activation) which, as it increases, shifts a viewer from boredom to engagement, to involvement, and to flow. So while appetitive activation might be smoothly increasing – the states of attention might be discrete. This state shift would be much like the qualitative change in a horse's gait as its speed increases. With increasing speed (the control parameter), a horse shifts from walking, to trotting, to cantering, to galloping. Both slow and fast walking exist – but the pattern and dynamics of limb motion do not change as long as the horse is walking. At a specific speed, the limb dynamics of walking become unstable and the horse makes a sudden change from walking to trotting, and so on. Each gait type has qualitatively different behavioral dynamics from the others. Even though speed increases, linearly, the change between gaits is sudden and qualitative. If this is the case for attention, we might see appetitive activation or its correlates increasing linearly but find that measurable components of attention are changing suddenly. If this is the case, then the question becomes: 1) For each individual – how much time is spent in each of these attentional states over time in the co- vs single-viewing condition (i.e. is an individual's attractor depth for the different states changing as a function of co-viewing)? 2) Does the number of individuals in each of these states vary over time as a function of co- vs single-viewing (i.e. is the system's attractor depth of the different states changing as a function of co-viewing)?

Once our research questions have become DST-inspired, our research design will change accordingly. When using a linear approach, we try to control all third variables in order to identify the causal contribution of a single variable. Using the DST assumptions, we want to observe behavior in multiple contexts to see what it does and how behavior changes from one context to another. Cohen and Lancaster (2014) conducted an interesting GLM/DST hybrid study to determine if individual differences in need for company and need to belong predicted whether people were more likely to co-view in person or over social media. From a DST perspective, this is a question about how two individual differences (which might be linearly increasing control parameters or individual differences in initial conditions) influenced the stability of two behavioral attractors (in person co-viewing and social media co-viewing). The authors conducted an online questionnaire to determine the frequency with which people co-viewed in person and over social media and their need for company/belonging. This frequency data could have and still could be used to determine the relative within-individual stability of each of the two behaviors and the overall depth of the two attractors in the system. In this study the authors went on to use a regression model to test the predicted relationship while controlling impacts from other unknown factors. How else might this data have been analyzed? One possibility would have been to look at the distributions of the ratio of time spent co-viewing in person and on social media. What is the distribution of ratios? Is it normal? Or, does it for example, have multiple modes? Perhaps a group of people with relatively equal levels of in person and social media co-viewing, and two groups who predominantly use one or the other. This would suggest that some people simply co-view and medium doesn't matter, others prefer to co-view in person, or on social media, but not both. If these groups appear to exist, one might then look at the distribution of need for company and need for belonging within each group. Perhaps those who are high in need for company and need for belonging also need to co-view and will use whatever medium is available, while those with only a high need for company prefer in person co-viewing and those with only a high need for belonging prefer social media co-viewing. Again, adopting DST assumptions does not mean that we have to throw out our old data, it may only mean that we need to think about it and analyze it differently.

What might a completely converted DST researcher, starting from scratch, have done to answer this question? First, they would have collected, for each subject, dynamic data about the amount of time each individual spent co-viewing in all types of contexts including in-person viewing, social-media co-viewing, and other types of co-viewing such as co-viewing over voice or video phone or by text. At the same time, they would have tried to get data about the dynamics of each individual's needs for belonging/company. Perhaps some people have cyclical patterns of needs, while others have consistently high or consistently low needs. Next they would examine the data to identify the set of behaviors making up the co-viewing state space, the stability of each co-viewing behavior identified across and within individuals, and whether those patterns of stability in co-viewing behaviors change at different levels of need for belonging and company within the system and within individuals. Initial analyses might be done on small groups of people to look for behaviors and patterns of change. Eventually these analyses would help to determine if the individual states result from differences in initial conditions (i.e. how the person feels at the moment the opportunity to co-view occurs) or control parameters (i.e. linearly increasing variables that shift people from one behavior to another). In addition, these data might then help to provide estimates of parameters and weights as one approaches a level of knowledge that might allow one to begin to model the co-viewing/needs system.

To sum up, the GLM assumes linear causality and averages over people and often over time. Variability over time within individuals and across behaviors over time is the data that is *lost* when using the GLM. It is also the data that is *used* to investigate a dynamic system. What is noise for the GLM is the data the DST uses to understand the movement of individuals from state to state and the stability of those states over time in various contexts (Richardson, Paxton, & Kuznetsov, 2017; Valenza, Lanata, & Scilingo, 2012).

On system dynamics and bifurcations

In this section, we look at results of research on couples and parent-child co-viewing to illustrate a communication system that may have a bifurcation point (i.e. a point in time where some behaviors appear or cease to exist in the system). Research on family co-viewing suggests that co-viewing behavioral states may change as a function of family dynamics over the life cycle. Indeed, eventually DST analyses will need to examine communication systems across the life cycle to discover *all* the possible states a system can perform. In fact, because dynamic systems are mathematically described by pairs of differential equations and most of these pairs of equations cannot be solved analytically, dynamic systems are actually analyzed by numerically running them through time until the final attractor appears.

Mora, Ho, and Krider (2011) found that increases in the sum of the age of a couple and their socioeconomic status resulted in a linear decrease in co-viewing time. From this, the DST researcher knows that couples' co-viewing time depends on age and socioeconomic status and that as they increase, co-viewing becomes less stable. But we do not know anything about whether age and socioeconomic status are causing qualitative differences in co-viewing behavior (that is the appearance and disappearance of co-viewing behavioral states across the life cycle) or simple changes in the depth of attractors within couples and within the system.

Next Mora et al. (2011) asked how differences in a couple's psychographic distance from one another and the number of children in the family influenced co-viewing behavior. They found that, *in families with children*, but not in families without children, an increase in psychographic distance leads to less time co-viewing up to a threshold after which co-viewing time increases. The authors explained that after the turning point, couples with children use co-viewing time for family conflict management. In childless families increasing psychographic distance between couples linearly decreases co-viewing time.

From a dynamic systems perspective, we now see that Mora and colleagues have identified at least one qualitatively different type of co-viewing – co-viewing for conflict management. Their explanation suggests that prior to the threshold which brings about co-viewing for conflict management, a different kind of co-viewing might have been occurring. They also identified a linearly increasing control parameter (psychographic distance between couples) which leads to decreasing amounts of co-viewing (loss of stability) for families without children and moves the system from one type of co-viewing to the newly discovered co-viewing for conflict management for families with children.

The next step is to ask how many co-viewing states there are. In other words, what is the state space of co-viewing? We can begin to answer this question by re-examining the literature. Have other types of co-viewing been identified? Perhaps co-viewing for education, entertainment, or companionship. The literature will also tell us what variables are related to changes in each type of co-viewing. Some of these variables, like psychographic distance, might look like possible control parameters, others, like having children, might be requisite initial conditions. After reviewing the literature, research could be done to determine if these different types of co-viewing exist and if they are behaviorally distinct leading to a description of the state space of the system.

Next research can be designed to observe systems over time to determine the stability of the states within the system and individuals and to assess the plausibility of suggested third variables as initial conditions or control or order parameters. We might begin by hypothesizing that psychographic distance is the control parameter that moves couples from one co-viewing state to another. For example, we might test the hypothesis that couples with small psychographic distance tend to like the same television content and therefore co-viewing for entertainment is a stable attractor. At the same time, we might find that the message content matters. Perhaps when the television content is a chick flick or a wrestling match (that is something that appeals to one but not the other member of the couple) one member of the couple might shift from co-viewing for entertainment to co-viewing for companionship. As psychographic distance increases we might find that co-viewing for entertainment remains but that co-viewing for companionship becomes unstable and eventually disappears. We might go on to use the literature to reconceptualize our thoughts about co-viewing in families with children. The important point to be made here is not what those hypotheses might be but rather that the place to start our DST investigations is in the copious amounts of well conducted research we have already done. This body of work will not only help us to identify the states that may exist but also to find plausible important contextual and initial conditions and order and control parameters to test. And in some cases reanalysis of previously collected data will enable initial tests of these new hypotheses.

Further, our re-conceptualization, as described above, may very well discover that different types of families have different sets of co-viewing attractors. This would tell us that the system has bifurcation points where behaviors can disappear or appear. In short, adopting a DST perspective informed by existing literature can produce interesting DST inspired versions of existing communication theories and sometimes allow for initial testing of the new predictions.

Conclusions

The first goal of this paper is to explain that using DST to study communication systems does not provide a new theoretical framework for studying communication. Rather, it provides a new analytical theory of change and causation that has different assumptions about the nature of change and causality. When we change our assumptions, what was noise becomes data and our research questions, study designs, data collection, analysis, and results all change. Given that many natural phenomena in both the physical and biological sciences appear to operate as complex systems, and that human communication is essentially an evolved biological and psychological complex system, it makes sense to think that many aspects of human communication behavior might be more in line with the assumptions of the DST than those of the GLM.

We also hope to have demonstrated that you can adopt a DST approach without becoming a dynamic systems modelling expert. Much of the initial work involved in the DST approach is qualitative and empirical (Thelen & Smith, 1994). Following the model spelled out by Thelen and Smith, Lang, et al. (2018, in press) have undertaken these sorts of quasi qualitative empirical secondary analyses of existing data to examine how video game play stabilizes and destabilizes real world behaviors. The steps have been illustrated in this paper using the co-viewing literature. First, define and observe a system over time to identify its qualitatively different behavioral attractors and plausible candidates for variables that might function as important initial conditions and order and control parameters. Second, observe the system in multiple contexts where it naturally occurs to find important contextual factors. Third, determine the system and individual levels of stability for the attractors. Fourth, test hypotheses about plausible control, order, individual difference, and contextual variables. Fifth, eventually, hopefully, build a model.

The beauty of DST is that it tells us to expect what we already know about our data. If we put people in the same room, at the same or at different times, and have them experience the same messages, they rarely do the same things in response. DST provides a tool that not only allows us to *expect* this variability in responses, but also uses that variability to understand the causal dynamics of the system.

Finally, this paper has hopefully demonstrated that the work the field has done to date has not been wasted. We have developed rich and meaningful theories which can be reconceptualized using these new assumptions, after which we can use the wealth of empirical data available to identify and study the systems related to questions we are interested in. The problems we are experiencing are not theoretical, we have identified many processes and effects that help explain the messiness of our data. This paper suggests that the problem is that communication systems are not amenable to being analyzed by the GLM because, when we do so, we are averaging over the variability that is the main indicator of the existence of, and tool for understanding how a dynamic system operates.

Note

1. Words frequently uttered by Julia Fox, Indiana University Assoc. Prof. of Communication Science, and attributed by her to her mentor Michael Shapiro, Professor of Communication at Cornell.

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